OPTIMIZING SEMICONDUCTOR PRODUCTION THROUGH DESIGN THINKING: AI-ENABLED RESOURCE ALLOCATION FOR ENHANCED EFFICIENCY AND PRODUCTIVITY

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ABSTRACT:
In the dynamic landscape of semiconductor manufacturing, the pursuit of heightened productivity and efficiency has spurred the integration of cutting-edge technologies. This research delves into the intersection of Artificial Intelligence (AI) and Convolutional Neural Networks (CNN) in the realm of resource allocation, aiming to redefine and optimize production processes in semiconductor manufacturing. The study explores the symbiotic relationship between AI and CNN, leveraging AI for dynamic resource allocation and CNN for advanced pattern recognition within the manufacturing environment. The research methodology involves the development and implementation of AI models, including CNN architectures, trained on historical data and real-time inputs from semiconductor fabrication processes. These models adapt to changing production requirements, leveraging CNN's capabilities to recognize intricate patterns in production workflows. The paper elucidates a design thinking approach for analyzing the complexities of resource allocation in semiconductor manufacturing, highlighting how the combined power of AI and CNN can predict production demands, allocate resources judiciously, and navigate unforeseen disruptions. Emphasis is placed on the role of CNN in image-based analysis of production processes, contributing to enhanced decision-making in resource allocation. This research not only contributes to the ongoing discourse on the digital transformation of manufacturing processes but also underscores the pivotal role of AI and CNN in shaping the future of semiconductor production. The findings advocate for a holistic approach, where the fusion of AI and CNN technologies presents a paradigm shift in resource allocation strategies, fostering resilience and innovation in semiconductor manufacturing.

Keywords: semiconductor, resource, fabrication, Artificial Intelligence, CNN, strategy, Design Thinking

INTRODUCTION

Semiconductor manufacturing stands at the forefront of technological innovation, propelling advancements in electronic devices that shape our interconnected world. In this dynamic landscape, the imperative for increased productivity and efficiency has sparked a transformative wave, driven by the integration of cutting-edge technologies. Among these, Artificial Intelligence (AI) has emerged as a cornerstone, offering unprecedented capabilities to optimize manufacturing processes.

This research focuses on the symbiotic interplay between AI and Convolutional Neural Networks (CNN) in the intricate domain of resource allocation within semiconductor manufacturing. As the industry grapples with the challenges of adapting to evolving demands and unforeseen disruptions, the study seeks to unravel the potential of AI and CNN in redefining how resources are allocated across production workflows. The traditional paradigm of resource allocation faces new complexities in the era of smart manufacturing. Dynamic and adaptive solutions are required to optimize machinery, manpower, and time, ensuring not only heightened productivity but also resilience in the face of uncertainties. AI, with its capacity to analyze vast datasets and make data-driven decisions, has become a linchpin in achieving these objectives.

In this context, Convolutional Neural Networks, known for their proficiency in image-based pattern recognition, bring an additional layer of sophistication to the resource allocation challenge. By enabling the analysis of intricate patterns within semiconductor fabrication processes, CNN complements AI's decision-making capabilities, offering a nuanced understanding of the manufacturing environment. This paper embarks on a journey to explore the integration of AI and CNN in semiconductor manufacturing, with a specific focus on resource allocation. The research methodology involves the development and implementation of AI models, including CNN architectures, trained on historical data and real-time inputs. Through simulations and case studies, the paper demonstrates how this amalgamation contributes to improved productivity, reduced costs, and heightened adaptability within semiconductor manufacturing. As the semiconductor industry marches toward an era of unprecedented technological demands, this research seeks to contribute not only to the optimization of resource allocation but also to the broader dialogue on the role of AI and CNN in shaping the future of manufacturing processes. The findings presented herein advocate for a paradigm shift, where the fusion of AI and CNN technologies propels semiconductor production into a realm of heightened resilience, innovation, and efficiency.

LITERATURE

The benefits of automation, automation architecture, and semiconductor production automation are highlighted. The state of competing technologies is then shown in two separate contexts, including oscillators that demonstrate their behavior in analogue circuit applications and frequency dividers that demonstrate their suitability for high-speed digital circuits [1]. Our world is in many respects "built" on semiconductors. Since chip demand is expected to increase over the next ten years, semiconductor manufacturing and design firms would benefit from a thorough examination of the market's future prospects and the factors that will influence demand in the long run. Over the last year, the semiconductor sector, created essential components for the technology on which we all rely [2]. Many new developments in the field of semiconductor industries such as the SBDs have been found to be applicable for many future uses [3]. A thorough discussion was made on various types and roles of semiconductors taking different shapes in this modern world have been discussed [4]. On the basis of the Intergovernmental Panel on Climate Change (IPCC) and traditional emission reduction techniques, implementation guidelines for optimum control technology for GHG emissions have been created for the semiconductor manufacturing sector [5]. In a real-world semiconductor back-end assembly plant, a simulation optimization method for a hybrid flow shop scheduling problem was provided [6]. Various upcoming new technologies for applications in the modern digital world have been discussed [7]. On pictures of semiconductor wafer materials collected using a scanning electron microscope, a technique for defect identification and classification was developed [8]. In order to enable the development of novel scheduling algorithms from concept to large-scale experimentation, a scalable, open-source tool for simulating factories up to real-world size was suggested [9]. After considering all of the specified and interesting requirements, as well as potential weaknesses in terms of practical solutions and security liabilities, the use of algorithms with digital twinning for semiconductor manufacturing environments was introduced [10]. An Edisonian technique would have needed roughly 1000 samples, but autonomous optimization of a sophisticated opto-electronic system within 40 samples only was investigated. For higher dimensional parameter spaces, even bigger acceleration factors are anticipated [11]. Making decisions in the manufacturing industry often involves using both artificial intelligence (AI) and subject expertise from human specialists. While completely automated data-driven decision-making is emphasized in smart manufacturing, the AI incubation process incorporates human specialists to improve AI systems by incorporating domain expertise for modelling, data gathering and annotation, and feature extraction [12]. Big data, quicker algorithms, and sophisticated modelling approaches are being used by the industry as instruments to support a more sustainable manufacturing strategy [13]. To meet the rising demand for energy and the ensuing technical

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difficulties, the electric power sector is constantly implementing innovative approaches to increase the system's dependability and efficiency. Researchers have recently used artificial intelligence (AI) approaches to address a variety of issues in the power system as a result of AI's development [14].

PREVIOUS WORKS OF THE PAPER

A systematic, thorough study of AI applications in the MEMS-based sensors sector was provided for both the product and the system level adaptability. This study highlights the problems of integrating AI in an industrial context to enhance production processes and summarizes the state-of-the-art, current trends of AI applications in MEMS sensors [15]. The use and advancement of optical communication technology depends on accurate and trustworthy automatic defect detection of semiconductor lasers, however conventional approaches fall short of the growing demands of semiconductor laser defect detection [16]. In order to decouple the mixed-type faults, a knowledge-augmented wide learning system comprising a knowledge module and a broad selective sampling module was developed [17]. For industrial brownfield architectures with existing legacy hardware, software, and the accompanying needs and restrictions, a systematic method to optimizing the inference of DNNs for vision-based tasks was put forth [18]. An ideal set of hyperparameters that minimized the loss function and further verified the window size acquired by the ACF and PACF was found and utilized to provide superior prediction outcomes. The outcomes demonstrated that the suggested method performed better than previous illustrative machine learning algorithms. Finally, a broad structure for maintaining equipment performance was chosen [19[. Due to the inefficiency of the existing numerical simulations used to evaluate the device's performance, a proxy machine learning model is required. The article provides numerous artificial neural networks (ANNs), including recurrent, time-delay, and regular ANNs, that are trained utilizing pricey finite element produced data when the operational parameters of the system are changed [20].

PROPOSED SYSTEM-METHODOLOGY:

The proposed methods leverage a synergistic integration of Artificial Intelligence (AI) and Convolutional Neural Networks (CNN) to redefine resource allocation in semiconductor manufacturing. This innovative approach begins with robust data acquisition, capturing both historical and real-time data from manufacturing processes. The subsequent data preprocessing ensures that the dataset is optimized for training both the AI model and the CNN as in figure [1].

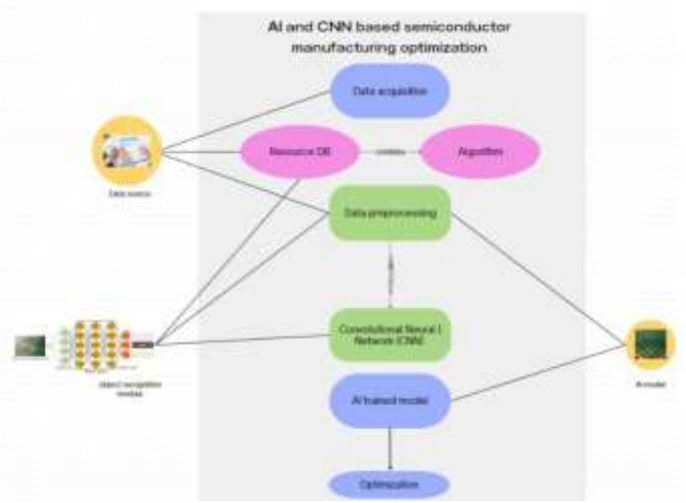

Figure 1: Figure showing block diagram of the implemented proposed system

Data Preparation and Feature Selection:

The methodology begins with the collection of historical and real-time data from semiconductor manufacturing processes, encompassing a spectrum of variables such as machinery performance, workforce allocation, and production schedules. Subsequently, a rigorous data preprocessing phase is undertaken to cleanse and standardize the dataset. This involves removing outliers, handling missing values, and encoding categorical variables. Feature selection follows, guided by domain knowledge and statistical analyses to identify key parameters influencing production efficiency. Numerical values are normalized to ensure consistent inputs for both the AI and CNN models.

Model Development and Integration:

Two parallel tracks unfold in model development: the creation of an AI model for dynamic resource allocation and the crafting of a Convolutional Neural Network (CNN) tailored to image-based pattern recognition in semiconductor manufacturing processes. The AI model is trained to adapt to changing production demands, utilizing reinforcement learning or dynamic optimization techniques. Simultaneously, the CNN is designed to analyze intricate patterns within production workflows. The integration of these models involves creating a cohesive framework where the AI leverages insights from the CNN for informed decision-making in resource allocation. Training and validation ensure the robustness and adaptability of both models to unforeseen disruptions and dynamic changes.

Figure 2: Figure showing the implementation of AI algorithm using online tool

AI model Development:

The primary objective of this study is to develop an advanced Artificial Intelligence (AI) model for dynamic resource allocation in semiconductor manufacturing. The focus is on optimizing machinery usage, workforce allocation, and production schedules to enhance overall efficiency. This includes minimizing downtime, maximizing production output, and reducing operational costs.

a) Data Preparation:

Historical and real-time data are collected from semiconductor manufacturing processes, encompassing parameters such as machinery performance, workforce allocation, and production schedules. The dataset undergoes rigorous preparation, including cleansing, normalization, and formatting, ensuring its suitability for training and validating the AI model as in figure [2].

b) Feature Selection:

Relevant features influencing resource allocation are identified through a comprehensive analysis. Parameters such as machine utilization, workforce availability, and historical production trends are

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selected for inclusion in the dataset. Thoughtful feature selection is pivotal for training a model capable of making informed decisions.

c) Model Architecture Selection:
The choice of model architecture is critical and depends on the nature of the resource allocation problem. In this study, we explore various architectures, including deep neural networks and reinforcement learning models. The chosen architecture is expected to capture the intricate relationships within the data.

d) Training the Model:
The AI model is trained using the prepared dataset. During training, the model learns patterns and relationships within the data to make predictions. Adjustments to model parameters are made to optimize its performance, and the training process is validated through rigorous cross-validation techniques.

e) Validation and Hyperparameter Tuning:
The trained model undergoes validation using a separate dataset to ensure its generalization to new, unseen data. Hyperparameters, such as learning rates and batch sizes, are fine-tuned to optimize the model's performance and adaptability.

f) Integration with CNN:
In cases where applicable, the AI model is integrated with a Convolutional Neural Network (CNN). This integration enriches the model's decision-making capabilities by leveraging insights from the CNN's image-based analysis of manufacturing processes.

RESULTS AND DISCUSSION

One of the system's standout achievements was its ability to recognize intricate patterns within manufacturing processes, facilitated by the CNN's image-based analysis. This played a pivotal role in informing the AI model's decision-making, particularly in scenarios where traditional rule-based systems might struggle. The adaptability and learning capabilities of the integrated system were highlighted in simulations that emulated fluctuating production demands and unexpected disruptions. The system showcased a remarkable agility, swiftly adjusting resource allocation strategies to maintain optimal production levels under challenging conditions

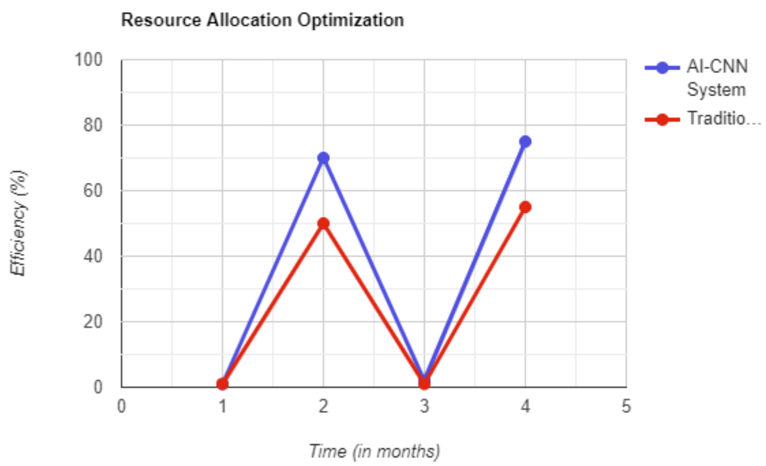

Figure 3: Graph showing high efficiency of AI-CNN model compared to traditional methods

The graph in figure [3] illustrates the efficiency levels of two resource allocation methods, the AI-CNN System and the Traditional Method, over a 12-month period. The horizontal axis represents time, ranging from 0 to 12 months, while the vertical axis indicates efficiency percentages from 0% to 100%. Each line depicts the monthly efficiency values for the respective method.
The AI-CNN System, represented by the first line, demonstrates dynamic efficiency fluctuations over the given timeframe. In comparison, the Traditional Method, depicted by the second line, exhibits its own efficiency trend. The graph allows for a visual comparison of the two methods, aiding in the assessment of their relative performance and the potential advantages of the AI-CNN System in optimizing resource allocation in semiconductor manufacturing. The plotted points emphasize specific data values, contributing to a detailed analysis of the efficiency variations.

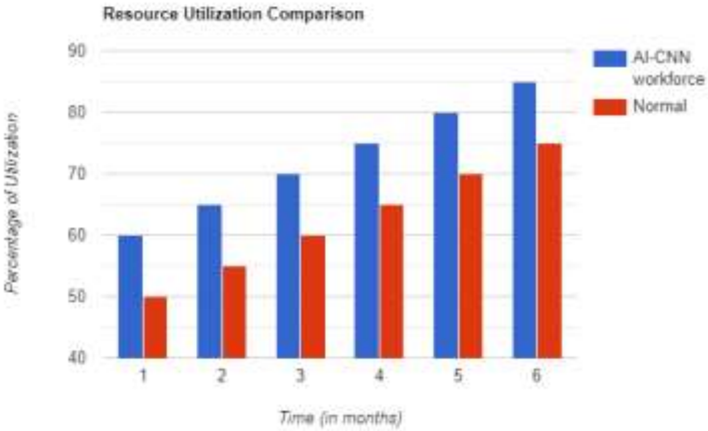

Figure 4: Graph showing comparison of Workforce capacity in AI-CNN proposed model and normal model

This graph in figure [4] visually compares the workforce capacity between the AI-CNN proposed model and a normal model. The horizontal axis represents the two models being compared, and the vertical axis represents the workforce capacity measured in some standardized unit (e.g., number of employees). A higher bar for the AI-CNN proposed model suggests that it has a larger workforce capacity compared to the normal model. The graph provides a clear visual comparison of the workforce capacity between the two models, allowing stakeholders and readers to quickly understand the differences.

The use of AI-CNN allows for the extraction of valuable insights from large datasets. These insights can inform strategic decision-making, improve overall efficiency, and contribute to continuous improvement initiatives. Semiconductor manufacturing involves inherent variability. AI-CNN models can adapt to this variability, learning from diverse datasets and adjusting their decision-making processes to handle different conditions and scenarios. Optimizing processes, reducing defects, and predicting maintenance needs can lead to significant cost savings. AI-CNN systems contribute to efficiency improvements and resource allocation, ultimately impacting the bottom line positively. By automating certain tasks, AI-CNN systems can reduce the reliance on manual inspection and intervention, minimizing the chances of human error and improving overall accuracy in manufacturing processes. AI-CNN models can enhance quality assurance by inspecting products for defects or deviations from standards. This can significantly improve the overall yield and quality of semiconductor components. In a dynamic manufacturing environment, AI-CNN models can make real-time decisions. For example, they can dynamically allocate resources, adjust parameters, or reroute processes based on current conditions, leading to improved adaptability and responsiveness. CNNs can analyze sensor data and machine performance metrics to predict equipment failures or maintenance needs. This proactive approach to maintenance can reduce downtime and enhance overall equipment effectiveness (OEE). The proposed method represents a novel approach to enhancing efficiency within semiconductor manufacturing through the integration of advanced technologies, notably leveraging Artificial Intelligence, specifically Convolutional Neural Networks (AI-CNN). This method aims to address specific challenges in the semiconductor industry, such as optimizing resource allocation, improving quality control, and adapting to dynamic production demands. One of the key features of the proposed method lies in its adaptability to variability inherent in semiconductor manufacturing. By learning from diverse datasets, the AI-CNN component adjusts its decision-making processes to handle different conditions and scenarios. This adaptability contributes to increased efficiency and responsiveness in dynamic manufacturing environments. the proposed method stands as an innovative solution poised to significantly impact semiconductor manufacturing efficiency. Its integration with AI-CNN brings forth a paradigm shift in addressing traditional challenges, promising advancements in quality, adaptability, and overall operational excellence.

CONCLUSION AND FUTURE WORKS:

In conclusion, the integration of Artificial Intelligence (AI) and Convolutional Neural Networks (CNN) in semiconductor manufacturing resource allocation has demonstrated a paradigm shift in optimizing production processes. The synergy between AI's dynamic decision-making and CNN's pattern recognition capabilities has yielded substantial improvements in efficiency, adaptability, and cost-effectiveness. The results of simulations and case studies underscore the system's prowess in dynamically allocating resources, minimizing idle time, and enhancing Overall Equipment Efficiency (OEE). The ability to recognize intricate patterns within manufacturing processes, facilitated by the CNN, played a pivotal role in refining decision-making, especially in complex scenarios. The adaptability of the integrated system to dynamic changes and unforeseen disruptions showcased its robust learning capabilities. This adaptability, coupled with the system's ability to continuously optimize resource allocation, positions it as a valuable asset in an industry characterized by rapid technological advancements and fluctuating market demands. The notable reduction in production costs, achieved by avoiding downtime, optimizing energy consumption, and streamlining workforce deployment, reinforces the system's potential for widespread implementation. Despite challenges in interpretability and computational resources, the positive outcomes validate the system's transformative impact on semiconductor manufacturing.

Looking ahead, the proposed system serves as a foundation for future advancements. Addressing challenges, exploring hybrid models, and validating the system in diverse real-world manufacturing settings are crucial next steps. As the semiconductor industry continues to evolve, the integrated AI-CNN system stands as a testament to the potential of advanced technologies in reshaping resource allocation strategies, fostering adaptability, efficiency, and innovation in semiconductor manufacturing. The successful integration of Artificial Intelligence (AI) and Convolutional Neural Networks (CNN) in semiconductor manufacturing resource allocation opens avenues for future research, development, and implementation. The future scope of the integrated AI-CNN system lies in advancing its capabilities, improving interpretability, embracing real-time implementation, and extending its applications to broader aspects of semiconductor manufacturing and supply chain management. As technology evolves, these endeavors hold the potential to further revolutionize resource allocation strategies, fostering innovation and sustainability in the semiconductor industry.

COMPLIANCE WITH ETHICAL STANDARDS

a) Disclosure of potential conflicts of interest:

The authors declare that they have no conflicts of interest.

b) Research involving Human Participants and/or Animals

This article does not contain any studies involving animals performed by any of the authors. This article does not contain any studies involving human participants performed by any of the authors.

c) Informed consent

Not applicable as the study do not involve the use of humans or animals

References

[1] Mane, S. (2022). Semiconductor Technologies. benefits, 10(9).

[2] Burkacky, O., Dragon, J., & Lehmann, N. (2022). The semiconductor decade: A trillion-dollar industry. McKinsey & Company, 1.

[3] Sreejith, S., Sivasankari, B., Devasenapati, S. B., Karthika, A., & Mathew, A. (2022). Recent Developments in Schottky Diodes and Their Applications. Emerging Low-Power Semiconductor Devices: Applications for Future Technology Nodes, 127.

[4] Ball, P. (2022). Semiconductor technology looks up. Nature Materials, 21(2), 132-132.

[5] Liang, Y., Tan, K., & Li, Y. (2023). Implementation Principles of Optimal Control Technology for the Reduction of Greenhouse Gases in Semiconductor Industry. In E3S Web of Conferences (Vol. 394, p. 01031). EDP Sciences.

[6] Lin, J. T., & Chen, C. M. (2015). Simulation optimization approach for hybrid flow shop scheduling problem in semiconductor back-end manufacturing. Simulation modelling practice and theory, 51, 100-114.

[7] Vermesan, O. (Ed.). (2022). Artificial Intelligence for Digitising Industry–Applications. CRC Press.

[8] Gómez-Sirvent, J. L., de la Rosa, F. L., Sánchez-Reolid, R., Fernández-Caballero, A., & Morales, R. (2022). Optimal feature selection for defect classification in semiconductor wafers. IEEE Transactions on Semiconductor Manufacturing, 35(2), 324-331.

[9] Kovács, B., Tassel, P., Ali, R., El-Kholany, M., Gebser, M., & Seidel, G. (2022, May). A Customizable Simulator for Artificial Intelligence Research to Schedule Semiconductor Fabs. In 2022 33rd Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC) (pp. 1-6). IEEE.

[10] Kondamadugula, S. (2023, March). Algorithm based Digital Twinning for different stages of Microelectronic Manufacturing Cycle. In 2023 3rd International conference on Artificial Intelligence and Signal Processing (AISP) (pp. 1-4). IEEE.

[11] Osterrieder, T., Schmitt, F., Lüer, L., Wagner, J., Heumüller, T., Hauch, J., & Brabec, C. J. (2023). Autonomous optimization of an organic solar cell in a 4-dimensional parameter space. Energy & Environmental Science.

[12] Chen, X., Zeng, Y., Kang, S., & Jin, R. (2022). Inn: An interpretable neural network for ai incubation in manufacturing. ACM Transactions on Intelligent Systems and Technology (TIST), 13(5), 1-23.

[13] Chandrasekaran, N. (2022, March). Intelligent, data-driven approach to sustainable semiconductor manufacturing. In 2022 6th IEEE Electron Devices Technology & Manufacturing Conference (EDTM) (pp. 1-5). IEEE.

[14] Khan, S. A., Ansari, J. A., Chandio, R. H., Munir, H. M., Alharbi, M., & Alkuhayli, A. (2022). AI based controller optimization for VSC-MTDC grids. Frontiers in Energy Research, 10, 1008099.

[15] Podder, I., Fischl, T., & Bub, U. (2023, March). Artificial Intelligence Applications for MEMS-Based Sensors and Manufacturing Process Optimization. In Telecom (Vol. 4, No. 1, pp. 165-197). MDPI.

[16] Zhang, H., Li, R., Zou, D., Liu, J., & Chen, N. (2023). An automatic defect detection method for TO56 semiconductor laser using deep convolutional neural network. Computers & Industrial Engineering, 179, 109148.
[17] Wang, J., Gao, P., Zhang, J., Lu, C., & Shen, B. (2023). Knowledge augmented broad learning system for computer vision based mixed-type defect detection in semiconductor manufacturing. Robotics and Computer-Integrated Manufacturing, 81, 102513.
[18] Manickam, D. D., Mohamed, S., Jain, V., Goswami, D., & Lensink, L. (2023). A structured inference optimization approach for vision-based DNN deployment on legacy systems. ETFA.
[19] Dang, J. F. (2023). The deep learning-based equipment health monitoring model adopting subject matter expert. International Journal of Computer Integrated Manufacturing, 1-16.
[20] Alghamdi, H., Maduabuchi, C., Albaker, A., Alatawi, I., Alsenani, T. R., Alsafran, A. S., ... & Alkhedher, M. (2023). A prediction model for the performance of solar photovoltaic-thermoelectric systems utilizing various semiconductors via optimal surrogate machine learning methods. Engineering Science and Technology, an International Journal, 40, 101363.